SYNERGIZING LANDSAT-8 AND MODIS DATA FOR ENHANCED PADDY PHENOLOGY ASSESSMENT AND CROP FREQUENCY MAPPING: A FUSION OF PHENOLOGICAL INSIGHTS AND MACHINE LEARNING ALGORITHMS

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ABSTRACT:

The increasing demand for food and the impact of climate change underscore the need for intensified food production processes to continually address the growing population's requirements. A critical aspect of food planning involves the identification of cropping frequency, serving as a key strategy for enhancing food production. Remote sensing plays a pivotal role in capturing cropping frequency information by analyzing phenological characteristics recorded in band transformations. Furthermore, the integration of machine learning allows for the categorization of patterns derived from index responses, eliminating the need to individually detect each phenological phase. The study aims to assess the accuracy of multi-sensor data fusion using the STARFM algorithm and machine learning to produce dense time-series images combining Landsat-8 and MODIS downscaled imagery for mapping paddy's phenology and identifying paddy cropping frequencies. The phenology identification results demonstrate an accuracy range of 3-4 months for the Landsat dataset and less than 1 (one) month for the dataset resulting from its fusion with MODIS. Concurrently, the cropping frequency identification reveals an accuracy of 60%, 42.5%, 95%, 85%, and 100%, respectively, for Landsat phenology, fusion phenology, Landsat Decision Tree, fusion Decision Tree, and Random Forest for both datasets. This underscores the profound impact of data availability and quality on the accuracy of the obtained results. Dense time-series remote sensing data can be used for mapping cropping frequency to indicate the productive paddy areas which should be protected to ensure food security in the future.

Key-words: *Data fusion, Phenology identification, Cropping frequencies, STARFM, Machine learning.*

1. INTRODUCTION

The escalating demand for food aligns with the growth of the global population. Climate change poses a challenge that affects rice production, a staple crop in Asia. A decline in rice harvest yields and a shift in cropping (planting) seasons have occurred in parts of Indonesia as a consequence of climate change's impact on rice commodity agriculture (Khairulbahri, 2021; Y. Sari et al., 2021). Precise food planning is necessary to ensure the achievement of food security and resilience in line with SDG's number 2. Monitoring in terms of cropping frequency becomes crucial to support sustainable agricultural planning and serves as an approach to intensify the production of food crops especially rice that can be used to record number of production seasons per year. (Andrade et al., 2021). Field survey methods can provide accurate results because information is obtained directly from interview or by observing field phenomena, but it is not effective because it must be carried out periodically over a certain period.

The use of remote sensing images, which have the capability to record over a specific temporal range is the most promising tool for identifying cropping frequency. This can be done by identifying based on the reflection of objects on each band using band transformations such as EVI or NDVI,

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using a combination of each band transformations responses such as EVI with LSWI, building models based on historical records, and others (Huang et al., 2019; Y. Sari et al., 2021; Q. Wang et al., 2023). All these methods cannot directly produce the value of cropping frequency from vegetation, but rather use phenological characteristics to read the number of cropping frequencies. This leads to the need for phenology identification to generate cropping frequency information. Phenology information is accentuated using vegetation index band transformations in the form of responses to each growth phase to the selected band used. Some studies identify cropping frequency using phenology as a boundary between growth phases (Liu et al., 2018). In its development, the use of machine learning can be a method of extracting cropping frequency because it classifies based on the similarity of vegetation response patterns using the vegetation index. Unfortunately, several studies related to the use of machine learning have developed a lot for the identification of types of agricultural plants and only a few have used it for the identification of cropping frequency or planting patterns (Alami Machichi et al., 2023; Tariq et al., 2023; Tufail et al., 2022).

The identification process based on both phenology and machine learning necessitates accurate data quality to represent the detailed occurrence of vegetation growth. The use of free and available image data such as Landsat-8 medium spatial resolution images has limitations in the temporal aspect and is prone to cloud interference as a result. Meanwhile, good temporal resolution images, such as MODIS, do not have good spatial resolution, making them prone to object misclassification (Yin et al., 2019). The unavailability of free data in the appropriate spatial and temporal resolution aspects leads to the need for a multi-sensor data fusion method with complementary spatial and temporal resolutions. Various data fusion methods have been developed and are generally divided into three basic methods: weighted function-based, unmixing-based, and dictionary-pair learning-based (Hou et al., 2019). STARFM-a weighted function-based methods that weight the spatial and temporal aspects, thus capable of reconstructing multi-time data that have gaps and then producing images with good spatial and temporal resolution, developed by Gao et al. (2006) has been widely used and has shown success in producing synthetic data like Landsat which has good spatial and temporal resolution for identifying phenological events. Similar studies utilizing STARFM have demonstrated promising results in generating images with adequate spatial and temporal resolution, particularly for detecting phenology (Gallagher, 2018; Onojeghuo et al., 2018; Son et al., 2016; Vincent, 2021). In addition, downscaling MODIS and Landsat-8 data can produce a high-quality time-series data since MODIS and Landsat have similar orbital characteristics with only 30-minutes time difference when crossing equator (Hwang et al., 2011).

This research emphasizes on the identification of cropping frequency based on phenology and machine learning methods, utilizing Landsat-8 OLI images and the results of fusion with daily MODIS using the STARFM algorithm. The novelty of the research lies in the exploration of the effectiveness of downscaling MODIS data for extracting phenological metrics of paddy fields, and the comparison of phenological analysis and machine learning for identifying paddy cropping intensities. This study analyzes the necessity of conducting data fusion for obtaining dense time-series data to detect phenological metrics and subsequently, identify the paddy cropping intensities. Data fusion is carried out under wet climatic conditions with the Moderate La Nina phenomenon, which causes high cloud cover and rainfall in 2021, thereby affecting data availability.

2. STUDY AREA

This study was conducted in a portion of the protected paddy field area (LSD) in Sragen Regency, Central Java Province (110°45" and 111°10" E, 7°15" and 7°30" S), referring to the LSD data of 2021 (**Fig. 1**). The protected paddy field area is limited to areas with flat slope gradients and located around the Bengawan Solo River to avoid the influence of slopes on spectral responses and heterogeneity of agricultural commodities. Various rice varieties are developed in the LSD of Sragen Regency, including IR64, Inpari 32, PP, Ciherang, Tunggal, Mikonga, Wiapu, Sintanur, and others. All of them have a uniform rice age, ranging from 75-95 days. Being around the Bengawan Solo River and supported by the dominant characteristics of fertile soil due to the volcanic activity of Mount Lawu, Sragen Regency has become a rice-producing region that supplies national needs.

Referring to the research by Murti, 2014 and the geoportal data of Sragen Regency, it is known that Sragen Regency has three main landforms, namely volcanic in the southern part, fluvial in the middle, and structural-denudational karst in the northern part. The specific research area is located on the fluvial landform associated with the Bengawan Solo River and the volcanic landform associated with Mount Lawu. Topographically, the central area, which is a fluvial landform, has a gentle to flat relief with a slope of <8%, and the southern area, which is a volcanic landform, has a rolling to hilly relief with a slope of >15%. In relation to the landform of the study area, this forms several types of soil suitable for rice plants, namely grumusol, alluvial, and latosol. In relation to its slope factor, the research study area is part of the Bengawan Solo River basin. The central part of Sragen Regency or the northwest part of the study area is directly crossed by the main river, the Bengawan Solo River. This allows the surrounding rice fields to have sufficient water availability throughout the year. Furthermore, the slope also affects the size of the paddy field plots, which contributes to the mixing of land cover in one pixel. The paddy field plots in the research area tend to be larger around the Bengawan Solo River. Moving away to the south, which has a volcanic slope landform, results in the southern plots tending to be smaller than the south. The reason for choosing the area for the study area is based on the size of paddy fields (plot) which is large enough around 400m2 (Murti, 2014), so that it can reduce the heterogeneity of each paddy plot related to one pixel of 30 meters spatial resolution of Landsat and the downscaled imagery, and the diversity of planting patterns in these areas, which has been controlled by the topography and landform in the areas.

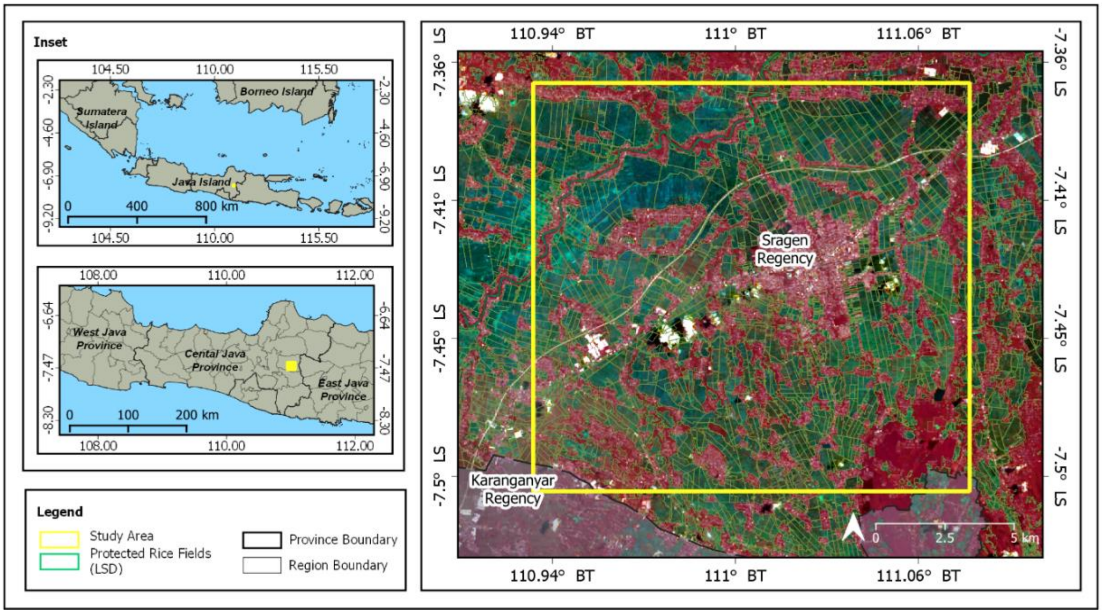


Fig. 1. Location of the Study area of Sragen Regency, Central Java Province, Indonesia (Basemap: Landsat-8 OLI/TIRS (2021-03-19) Composite 652).

3. DATA AND METHODS

3.1. Data Preprocesing

Landsat-8 OLI and MODIS image data require integrated and balanced pre-processing so that both can be used together for the purpose of image fusion. Google Earth Engine (GEE) as a cloud computing platform provides both datasets that are integrated with each other and can be used simultaneously. The use of GEE is based on the goal of pre-processing time efficiency, where it would take longer to process raw images such as geometric image correction, image pixel resampling, cloud masking, and index transformation. Further pre-processing stages of Landsat-8 OLI and MODIS images are carried out by referring to the research conducted by Gallagher (2018) based on the input dataset specifications for STARFM provided by the Agriculture Research Service (ARS) USDA.

3.1.1. Landsat-8 and MODIS Data Pre-processing

Landsat 8 Level 2, Collection 2, Tier 1 images with a temporal resolution of 16 days, and MODIS/061/MOD09GA Terra Surface Reflectance Daily Global 1km and 500m images with daily temporal resolution are used as the Landsat and MODIS datasets, respectively. Both have been corrected for surface reflectance and cloud masking has been performed using a bitmask on Google Earth Engine, prioritizing aspects of cloud, cirrus, and cloud shadow. The Landsat-8 images have a spatial resolution of 30m and MODIS images have a spatial resolution of 500m. To perform data fusion using STARFM, both need to adjust their spatial resolution to the highest, which is 30m, thus resampling is performed on the MODIS images using nearest neighbor.

3.1.2. Band Transformations

To highlight the characteristic features of each growth phase, this study does not use the original spectral response from each band, but instead uses the EVI and LSWI band transformations (Kou et al., 2017). EVI is an index that can suppress atmospheric and soil disturbances by using the blue, near-infrared, red bands indicated by $\rho_{NIR}, \rho_{RED},$ and ρ_{BLUE} in the Equation 1, and the constant coefficients G (2.5), L (1), and C (6 and 7.5) (Huete et al., 2002). Phenology-related research shows that EVI is sensitive during the greenup phase and provides higher accuracy results compared to NDVI for identifying areas with multi-cropping frequency (Huang et al., 2019; C. Wang et al., 2017). The use of EVI is used to identify the phenological phase of rice using the following formula:

$$\mathrm{EVI} = \mathrm{G} * (\rho_{NIR} - \rho_{RED})/(\mathrm{L} + \rho_{NIR} + \mathrm{C}_1\rho_{RED} - \mathrm{C}_2\rho_{BLUE}) \quad (1)$$

Meanwhile, LSWI is used to separate rice and non-rice phenology, thus generating the value of rice cropping frequency. The presence of SWIR and NIR bands indicated by $\rho_{NIR},$ and ρ_{SWIR} in the equation 2, can assist in identifying water content in vegetation or soil background (Bajgain et al., 2017; Chandrasekar et al., 2010). The use of EVI and LSWI has been widely used and has provided good results to show the inundation phase of rice (Dong & Xiao, 2016; Xiao et al., 2002). The formula for LSWI is as follows:

$$LSWI = (\rho_{NIR} - \rho_{SWIR})/(\rho_{NIR} + \rho_{SWIR}) \quad (2)$$

3.1.3. Auxiliary Data

Vector data of some parts of the protected paddy field (LSD) in Sragen Regency based on the 2021 statute is used as the boundary of the research study area and to focus on the paddy field area. In addition, three meters resolution PlanetScope imagery is also used for indirect data accuracy testing. The PlanetScope image used has been corrected for surface reflectance at the analytic_sr asset level.

3.2. Processing Steps

3.2.1. Data Fusion using STARFM

The Spatio-temporal Adaptive Reflectance Fusion Model, or STARFM, is an algorithm developed by Gao et al. (2006). STARFM operates by calculating pixels, taking into account the spectral value similarity and spatial distance between pixels within a certain window kernel size. STARFM has two main parameters: the maximum search distance for spectral similarity between pixels and the number of land cover classes for spectral similarity testing on pure pixels (number of spectral slices). Several studies for common land cover (without snow) show that STARFM works effectively at a max search distance of 700-800 with a land cover number of slice 40-80 (Gallagher, 2018; Gevaert & García-Haro, 2015). Based on this, this study uses a spectral distance parameter of 750 and a number of spectral slices parameter of 40 in the STARFM formula as shown below. In relation to the use of the Gallagher (2018) algorithm and the use of the Landsat-8 OLI/TIRS and MODIS Terra datasets, the absence of the same recording on each day the two satellites record the study area leads to the pairing of the Landsat image (t) with the MODIS image (t-1).

The formula is expressed as follows:

$$L(x_{\omega/2}, y_{\omega/2}, t_0 = \sum_{i=1}^{\omega} \sum_{j=1}^{\omega} \sum_{k=1}^{n} W_{ijk} \times (M(x_i, y_j, t_0) + L(x_i, y_j, t_k) - M(x_i, y_j, t_k) \quad (3)$$

In the equation 3, $x_{\omega/2}, y_{\omega/2}$ denotes the center of the moving window, and the ω variable indicates the size of the moving window. W_{ijk} denotes the weight of each neighboring pixels which were calculated from the spectral, temporal and location distance from the center of the moving window, x_i, y_j denotes the pixel location in Landsat and MODIS, while t_0, t_k indicate the time of base/reference image (t_0) and time of downscaled image (t_k).

3.2.2. Phenology-Based Cropping Frequency Identification

The process of identifying phenology and cropping frequency is carried out in R Studio. Before entering the phenology identification process, the Landsat dataset and its fusion results are regularized and reconstructed into daily data first, so that a regular and sequential time series data is obtained. The regularization process and daily data reconstruction are carried out by applying the Spline 'fmm' interpolation method to the dataset. The Phenofit R Package is used to identify phenology in each growing season by eliminating false peaks using the season_mov function. The parameters used are default, with rough fitting using Whittaker and fine fitting using Elmore. According to Kong et al. (2020) the curve fitting is performed to handle data that has noise due to atmospheric disturbances or interpolation results due to rapid and drastic changes in value, specifically, the rough fitting is used to capture seasonal signal while fine fitting is used to remove the noise including fake peaks. Meanwhile, the process of extracting phenology information in the form of the start of the season (SOS) and end of the season (EOS) as boundaries for each growing season is carried out using the Threshold method, referring to (White et al., 1997), with a threshold of 0.5 to represent its SOS and EOS. Each band transformation in the form of EVI and LSWI is processed with all of these methods. The EVI index is used to identify phenology (SOS-EOS), while the cropping frequency is identified using LSWI index based on the repetition of one SOS-EOS cycle which also indicates the occurrence of one paddy growing season. According to Zhu et al. (2022) cropping frequency refers to the number of production seasons per year, and is calculated as one frequency when it goes through the planting to harvest phase.

3.2.3. Cropping Frequency Identification Based on Machine Learning Algorithms

The training data generated from the field survey is used to build a model using the Decision Tree and Random Forest algorithms. The Decision Tree (DT) is a classification algorithm widely used for land cover classification (Friedl & Brodley, 1997). DT performs classification using a decision tree consisting of a root node (attribute), branches, and a leaf node (class label) (Purwanto et al., 2022). Meanwhile, Random Forest is a development of the Decision Tree with more decision trees or using a combination of various tree models, thus it can overcome overfitting that occurs in the Decision Tree (Chang & Bai, 2018). Given the differences in data complexity, DT can perform classification with little training data, while RF has an advantage over DT for classifying complex data (Hehn et al., 2020; Q. Wang et al., 2018). The input data for machine learning algorithm modeling is the EVI and LSWI dataset from Landsat and the fusion results using default parameters. Machine learning will learn the patterns that emerge from the combination of EVI and LSWI from each Landsat image and fusion results.

3.2.4. Field Survey

Field surveys are conducted both directly and indirectly. Direct surveys are conducted by interviewing farmers or land cultivators. Around 41 farmers were interviewed to understand the planting time and cropping intensities of the land that they cultivated. In addition, additional validation data are carried out by identifying each occurrence of planting start (SOS) and harvest start (EOS) using visual interpretation on daily PlanetScope data. In the field survey, K-Means clustering algorithm is used to help facilitating sample distribution, which is then spread using the purposive sampling method, eventually obtaining as many as 99 field sample points with all the information on

SOS, EOS, and cropping frequency that occurred in one year, with interview results as the baseline and interpretation results as detailed information. Field survey data is scaled in months and days. For modeling purposes, the total number of samples is divided into training and testing with proportions of 60% and 40%, respectively.

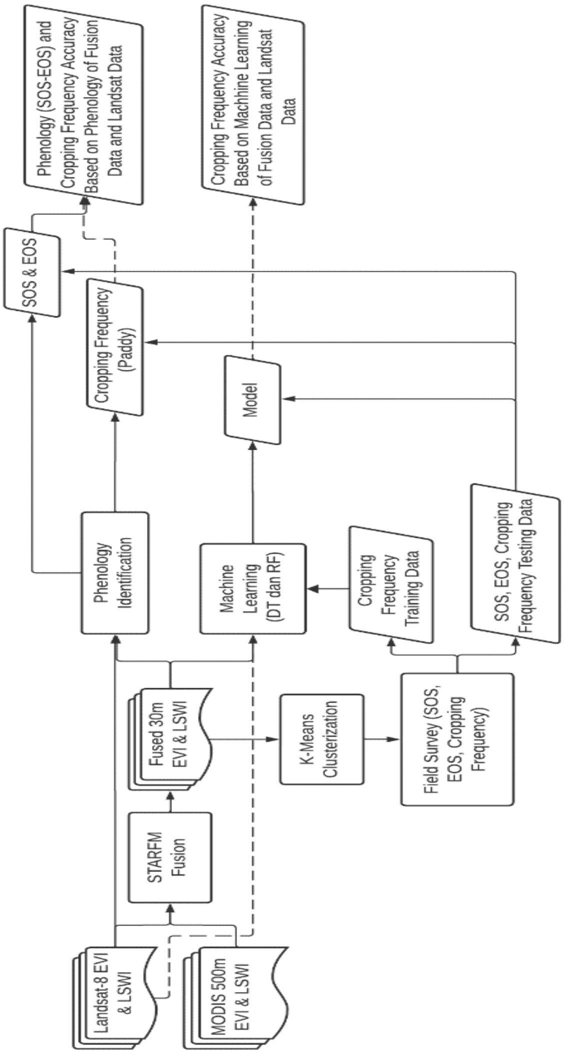


Fig. 2. Workflow of the study.

3.2.5. Accuracy Assessment

The accuracy assesment was performed on phenology parameters such as SOS and EOS results from identification using the root mean square error (RMSE), while cropping frequency information was conducted by constructing the confusion matrix by calculating the Overall Accuracy (OA), Producer Accuracy (PA), and User Accuracy (UA). RMSE was used for capturing the error margin between the actual values and predicted values. This has been used for various performance measure including for phenological analysis such as comparing the time differences between phenological metrics from satellite data and phenocam measurement (Czernecki et al., 2018, Browning et al., 2021). Testing on SOS and EOS was conducted to observe the magnitude of the difference in days between the test data and the identification results, while testing on cropping frequency is conducted to see how large the classification error is with the test data.

The workflow for this study can be found in **Fig. 2**.

4. RESULTS AND DISCUSSIONS

4.1. Fusion results using STARFM Algorithm

The fusion process using the STARFM algorithm are run automatically using the algorithm from Gallagher (2018). The use of default parameters shows good visual results on the fused data, as shown in **Fig.3**. Experiments were conducted to predict Landsat data on the same date with input data on the same date as well, and the results showed that STARFM was able to provide a display that was the same as its input data because there was no change whatsoever. The challenge that arises when using the Gallagher (2018) algorithm when using STARFM is in the Landsat-MODIS pair where the determination of good quality images is only based on the number of non-NA pixels from Landsat. This affects the fusion results where the NA value that has previously been converted to -32768 and is quite abundant in the MODIS image pair will contribute to the data fusion calculation. Meanwhile, in data where Landsat and MODIS contain NA, it will remain NA in the fused data results.

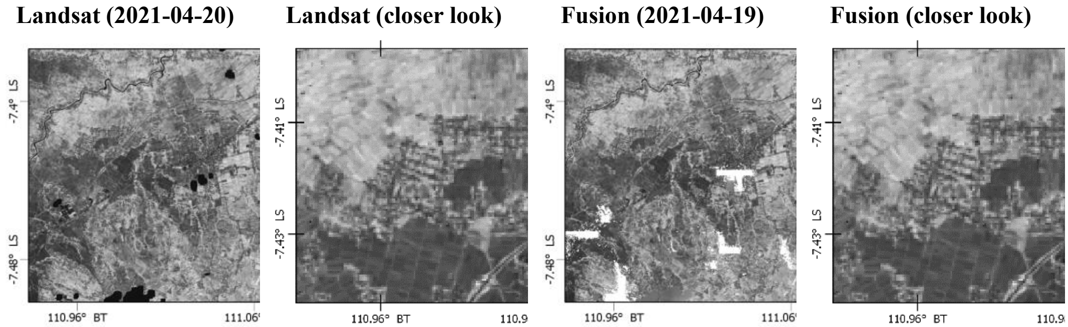
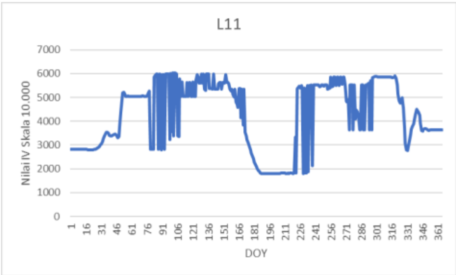


Fig. 3. The results of the fusion between Landsat and MODIS on the EVI index using the STARFM algorithm.

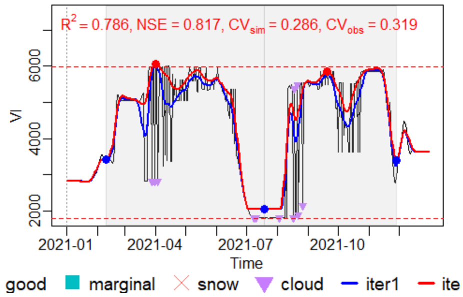
4.2. Phenology Identification for Cropping Frequency

The phenology identification process, which is run using the Phenofit R Package and uses Spline Interpolation as a method to fill in missing data or gap filling, shows success in identifying several growing seasons. Based on the results of the field survey, it is known that there are two main growing seasons in one year (Team, 2023) and Phenofit successfully captures this phenomenon. This can be seen in **Fig. 4(a)** where two growing seasons are successfully identified at that sample point. However, the Spline interpolation process in **Fig. 4(b**) which is used as input for Phenofit, provides results that are not quite appropriate due to the lack of image data at the beginning and end of the year, considering that clean image data is only available from the end of March (DOY 78) to October (DOY 304). The extrapolation performed by the Spline at the beginning and end of the year shows the presence of several small false peaks. Deficiencies in terms of interpolation are also found in the Landsat dataset, which provides a much longer data range compared to the original data range if compared to the linear interpolation method that will maintain the data range (Figure d). Both of these occurrences arise due to the Spline interpolation process used using the “fmm” method. Referring to R Documentation, this method is known to provide results that are not quite satisfactory for extrapolation because it considers four values before and after, which will impact the data range and accuracy of phenology identification. **Fig. 4(c)** shows the results of phenology parameter identification in the form of SOS and EOS. Phenofit does not provide processed ratio data as White et al. (1997) ratios the vegetation index into a range of 0-1. For this reason, the boundary line is not always balanced between SOS and EOS in the results.

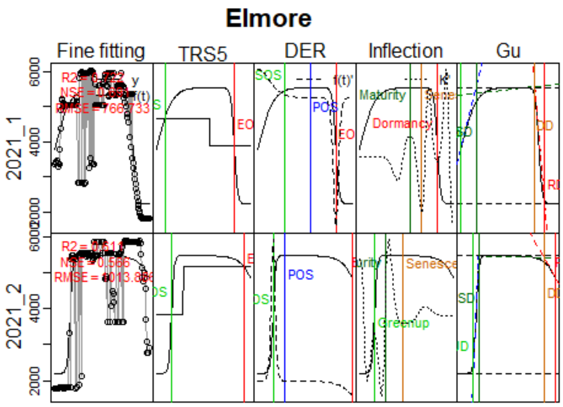
The use of a threshold of 0.5 on the interpolated data that has undergone curve fitting to minimize data noise produces accuracy as shown in **Table 1**. The results from the fusion show higher accuracy of the fused data compared to pure Landsat data. This indicates that the temporal aspect of the data affects the accuracy of phenology identification because the fusion results provide more detailed data in terms of temporal compared to Landsat data. The large error in this study may be caused by the interpolated data, which introduces a new data range.



(a)



(b)



(c)

Fig. 4. The interpolation results using the spline on the fusion data (a), the curve fitting results and identification of the growing season using R Package Phenofit (b), and the identification results of SOS & EOS using a threshold of 0.5 (c).

However, it should have been able to accurately capture the time range of planting (cropping) seasons 1 and 2, where based on field surveys, cropping season 1 starts in March-April and cropping season 2 starts in July-August. The study area is dominated by rice with an age of 75-100 days in fields with a seed planting time of 15-20 days. In other words, there should not be a data range around 120 days for one growing season considering that the seed planting process tends to be done at home or on a small part of the paddy field. For this reason, there is a difference of about ± a month between the field data and the interpolation results on the fusion, so it is clear that the interpolation process affects the results of phenology identification. This also applies to Landsat data which experiences a larger increase in data range compared to fusion data due to the lack of data availability.

Table 1.

Results of Phenological Identification Accuracy Using EVI Index.

Dataset		**Landsat**		**Fusion**	
Phenology Parameters		**SOS**	**EOS**	**SOS**	**EOS**
RMSE	**Monthly**	3.21	4.340	1	1.008
	Daily	101.478	138.270	27.086	31.840

4.3. Phenology-Based and Machine Learning-Based Method for Cropping Frequency Identification

Phenology information in the form of SOS and EOS from LSWI is used as a differentiator of growing seasons between rice and non-rice plants. LSWI will show a high reflection response during the irrigation phase and tends to decrease with the growth of rice (Sari et al., 2010). However, according to Nelson et al. (2014) besides specifically the presence of water in the irrigation phase as a characteristic of rice plants, the presence of water in large quantities occurs in almost two-thirds of its growth phases, namely vegetative and reproductive. The accuracy results from the identification method based on phenology and machine learning on the Landsat dataset and its fusion results show that the identification process using machine learning for both Decision Tree (DT) and Random Forest (RF) are able to provide higher accuracy compared to the identification process using phenology. Besides that, the accuracy on the Landsat dataset is higher than the fusion results on all methods (**Table 2**). In relation to the time spent processing the dataset using both methods, the use of machine learning provides a shorter time compared to phenology-based because it has to go through several processing stages.

Table 2.

Overall accuracy results of cropping frequency identification.

Dataset	Landsat Phenology	Fusi Phenology	Landsat DT	Fusi DT	Landsat RF	Fusi RF
OA (%)	65	42.5	95	85	100	100

5. DISCUSSION

Our research demonstrates a significant influence of data quality on the results of phenology identification and cropping frequency. The accuracy results of phenology identification show a large error ranging from 1-4 months in both datasets. Research related to phenology with similar thresholds tends to yield more accurate results. Huang et al. (2019) conducted identification for similar commodities with linear interpolation, EOS thresholds of 0 and 0.54, and SOS threshold of 0.26 and 0.16 for the first and second cropping seasons respectively, showing a substantial error range of around 9–13 days for EOS and 13–18 days for SOS, while in our research using Spline interpolation and similar threshold of 0.5 for both SOS and EOS. Therefore, the threshold and interpolation method play a significant role in the accuracy of phenology identification.

Fig. 5 shows that the results of Linear interpolation which maintain the data range differ significantly from the results of Spline interpolation. This discrepancy leads to a high error in phenology identification in the Landsat dataset, where the original values tend to be read as noise. Several phenology-related studies have been conducted using both interpolation methods. Nguyen-Sy et al. (2019) and Warter et al. (2023) used the Spline interpolation method while Wang et al. (2016) and Wang et al. (2022) used the linear interpolation method.

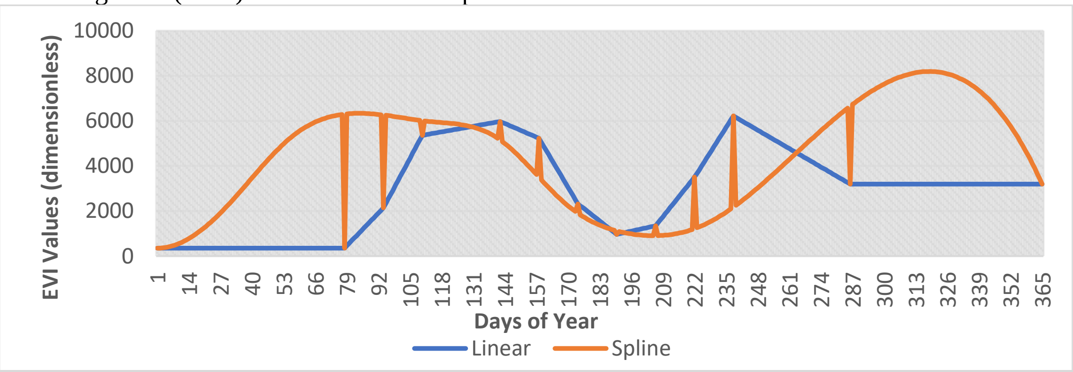


Fig. 5. Comparison between Spline and Linear interpolation using the Landsat dataset.

However, study conducted by Arjasakusuma et al. (2018) showed that spline produced the least accurate interpolation results. This indicated the needs for proper temporal interpolation method for phenology detection.

Comparing the accuracy testing results of phenology for the Landsat dataset and fusion results, it is found that the accuracy between the Landsat dataset and its fusion tends to be inversely proportional. The high accuracy of the Landsat dataset in phenology-based methods may be due to its ability to identify SOS and EOS that are not disturbed by noise in the form of false peaks, thus being able to identify both growing seasons but experiencing a large shift in data range as a result of the unsuitability of interpolation results. Similar accuracy is also found in machine learning-based methods where Landsat provides higher accuracy compared to fusion results due to the influence of low noise. Meanwhile, the Random Forest algorithm provides perfect results on both datasets, so it is estimated that this is due to the influence of simple data because it only involves 1-3 classes with patterns that do not vary much with not many samples.

Based on the confusion matrix results especially in omission error, the biggest error tends to occur in the cropping frequency class 2 (paddy planted twice a year), which is often classified as cropping frequency class 1 (paddy planted once in a year). In the phenology-based identification method, this can be caused by the failure to identify the second cropping season due to limited data availability, thus failing to reconstruct a complete growing season. This can be overcome by methods based on machine learning. Machine learning can identify pattern similarities based on the input data used, eliminating the need for a complete growing season. However, because the machine learning is used for supervised classification, it requires the data processor to ensure that the training and testing samples accurately reflect field conditions. The spatial distribution of the cropping frequency identification results can be observed in **Fig. 6**. From this, it becomes apparent that the identification results using machine learning methods, specifically Decision Tree and Random Forest, tend to yield similar outcomes. However, the most notable differences are observed in class 1 across both datasets. The area in the middle which is classified as class 1 in the Decision Tree results, is associated with the built-up areas. However, in the northern part, it remains within the paddy field area, characterized by large-sized plots. Compared to the results of the Random Forest, both areas tend to fall into class 2. The southern part is significantly influenced by the landform of the volcanic slope, resulting in smaller plot sizes and a strong dependence on the minimal availability of water in the dry season due to the elevation conditions. This impacts the absence of rice cultivation during the second cropping season. In the results of phenology-based identification, the Landsat dataset and fusion results show different visuals. The identification results of the Landsat dataset are more similar to the machine learning results compared to the fusion results. In accordance with the obtained accuracy results, noise significantly influences the classification results of the fused dataset, thereby limiting its ability to identify areas with grouped crop frequencies compared to the Landsat dataset or machine learning methods. However, it can provide a higher RMSE accuracy than Landsat in identifying the Start of Season (SOS) and End of Season (EOS).

The fusion phenology yielded different results as compared to the other methods, happened due to the changing curve after spline interpolation. This made the phenology metrics detection changed as showed in the **Fig. 6**. Apart from that, the influence of the presence of daily data and the growing season identification process from Phenofit which is based on the original interpolation results without smoothing, resulted in failure to identify the second growing season due to high noise and limited data to capture the complete second growing season because Phenofit only can read a complete growing season. Therefore, it only reads the first growing season and the detection of cropping frequency using phenological metrics become less accurate. However, machine learning is able to distinguish the patterns and only use the important variables to detect the cropping frequency, thus eliminating the error resulted from the spline interpolation and growing season identification process which is influenced by noise.

Future research could draw valuable insights from our study, particularly regarding the implications of temporal interpolation on time-series data. We utilized temporal interpolation techniques to fill in missing data, yet such methods possess the potential to alter the trajectory of the time-series data. Therefore, it is pertinent to assess the necessity of downscaling and temporal interpolation methods in mapping crop frequency based on the availability of clear images throughout the year. A complete distribution of clear images across different seasons facilitates accurate derivation of cropping frequency through machine learning algorithms. In addition, alternative downscaling approaches from other sensors should be explored, such as leveraging harmonized Landsat-Sentinel data, as highlighted by Claverie et al. (2021), which provides dense and consistent medium-resolution optical data. Additionally, combining active and passive sensors holds promise for generating more precise phenology and cropping frequency maps.

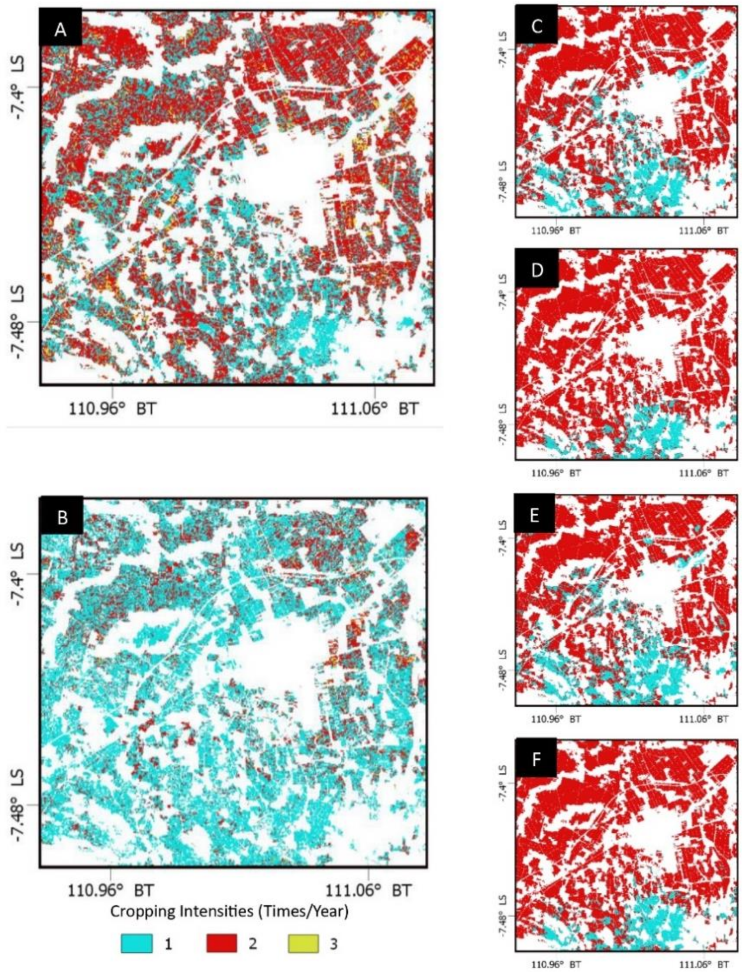


Fig. 6. Spatial distribution of cropping frequency in the study area (A) Landsat-Phenology, (B) Fusion-Phenology, (C) Landsat-Decision Tree, (D) Landsat-Random Forests, (E) Fusion-Decision Tree, and (F) Fusion-Random Forests.

6. CONCLUSIONS

Our study demonstrates the use of phenology-based and machine learning methods on the Landsat dataset and its fusion results with MODIS using the STARFM algorithm. Based on this, it is known that the aspect of data availability greatly affects the phenology identification results and the interpolation results. This leads to the need for high-frequency data and good data distribution for time series analysis. Furthermore, the use of fusion results to identify cropping frequency does not provide higher accuracy compared to Landsat data with an accuracy difference of 22.5%.

However, this cannot be directly concluded that the fusion results are unable to improve identification accuracy. Although the fusion data provides lower accuracy, it should be remembered that the high accuracy of Landsat data carries an error in the form of a larger shift in SOS and EOS time compared to the fusion results. Moreover, the fusion data' s inability to identify cropping frequency with high accuracy is largely due to the presence of noise, which hinders the successful detection of the growing season. Besides that, the identification process using cropping frequency using machine learning can provide excellent results. Its ability to read patterns is an advantage in terms of processing time effectiveness where it does not require a prior phenology identification process. The development of the use of machine learning and deep learning for phenology identification and related studies on noise reduction and time series data quality is expected to be developed for further research. In addition, the exploration using downscaled MODIS data and harmonized landsat-sentinel (HLS) can also be directed to get a more dense time-series data beneficial for phenology identification.

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